RETURNS TO SCALE IN SMALL AND LARGE U.S. MANUFACTURING ESTABLISHMENTS*

by

Sang V. Nguyen**

Arnold P. Reznek***

CES 90-11 September 1990

ABSTRACT

The objective of this study is to assess the possibility of differences in the production technologies between large and small establishments in five selected 4-digit SIC manufacturing industries. We particularly focus on estimating returns to scale and then make interferences regarding the efficiency of small businesses relative to large businesses. Using cross-section data for two census years, 1977 and 1982, we estimate a transcendental logarithmic (translog) production model that provides direct estimates of economies of scale parameters for both small and large establishments.

Our primary findings are that (i) there are significant differences in the production technologies between small and large establishments; and (ii) based on the scale parameter estimates, small establishments appear to be as efficient as large establishments under normal economic conditions, suggesting that large size is not a necessary condition for efficient production. However, small establishments seem to be unable to maintain constant returns to scale production during economic recession such as that in 1982.

*This article is based upon work supported by the U.S. Small Business Administration under grant 927/7577/SBA. Any opinions, suggestions and conclusions herein are ours, and do not necessarily reflect the views of the U.S. Small Business Administration or the Census Bureau. We thank Robert H. McGuckin for his constructive comments, and Carol Jones for her skillful typing.

**Center for Economic Studies, U.S. Bureau of the Census

***Statistical Research Division, U.S. Bureau of the Census

I. INTRODUCTION

The objective of this study is to assess the possibility of differences in the production technologies between small and large establishments in the U.S manufacturing sector. We particularly focus on estimating returns to scale and then make inferences regarding the efficiency of small businesses relative to large businesses.

We undertake this research for two reasons. First, standard industrial organization theory suggests that industrial long-run average cost curves are U-shaped or L-shaped. That is, over a certain range of output, small production units can expand their sizes to produce at declining average costs (increasing returns to scale). At a certain size, average costs flatten out (constant returns to scale). Beyond that size, average costs will increase at an increasing rate (decreasing returns to scale) as the production units continue to expand. Accordingly, this theory suggests that small production units can only exhaust economies of scale by expanding their sizes to some optimal level. This implies that small businesses are subject to inefficiency and eventually will fail, if they do not expand.

Yet, a growing body of evidence indicates that small businesses play a significant role in the U.S. economy, and that a large portion of economic growth and change comes from them. For example, Brock and Evans (1986) found that "Most of the 16.8 million businesses that filed tax returns in 1980 are small businesses by any standard. Eighty percent of 12.7 million are sole proprietorships, 60 percent of 1.4 million are partnerships, and 90 percent of the 2.7 million corporations filing in that year had annual business receipts of under $50,000" (p. 8). They also found that, in many industries, firms that had highest profits per dollars of sales in 1978 are those with 20-99 employees (see Brock and Evans, Table 2.1, p. 10). Brock and Evans' study appears to suggest that "large is not necessarily better."[1]

The 1987 Economic Report of the President cited recent research and concluded that "small is not necessarily inefficient and that small firms make contributions to overall efficiency" (p. 107). To explain the efficiency of small firms, the Report cited the following factor, among others:

> Because of their size, small firms are less likely to encounter problems that can arise from complicated multi-echelon management structures which are more common in large firms. These organization structures tend to increase the cost of transferring information within the firm and generally result in less flexible business decision making

process.

This means that, at least in some ways, small firms could be more efficient than larger firms -- they do not necessarily suffer from diseconomies of scale. Technically, this is equivalent to saying that efficient firm sizes may be small. This proposition, if true, has an important policy implication; policies to promote and support small businesses might be carried out without sacrificing efficiency, at least in terms of economies of scale.

This paper is an attempt to provide a direct test for the above hypothesis. To do so, we develop a transcendental logarithmic (translog) production model to estimate and compare returns to scale for both small and large production units. An advantage of the translog model is that it provides direct estimates of the scale parameter without imposing other unnecessary restrictions on the production technology such as linear homogeneity and constant elasticities of substitution.

The second reason for undertaking this study is that most previous empirical studies of economies of scale have often been based on published aggregate data. Such data may not reflect the activities of production units, and results based on these data are likely to be subject to aggregation bias. In this paper, we apply microdata at the plant level to our production analysis. These confidential data are extracted from the Census Bureau's Longitudinal Research Database (LRD), which is considered one of the most comprehensive microdata base available for the study of production. In particular, it contains data for establishments that are both "small" and "large" by any definition.

In this study, we choose to examine only five 4-digit SIC industries and use cross-section data for two census years, 1977 and 1982. Our experiments with the data led us to select the following five four-digit industry groups:[2] (1) SIC 2335: Women's, Misses' and Juniors' Dresses; (2) SIC 2511: Wood Household Furniture, Except Upholstered; (3) SIC 2711: Newspapers; (4) SIC 3573: Electronic Computing Equipment; (5) SIC 3662: Radio and Television Transmitting, Signaling, and Detection Equipment. We select these data and industries mainly because we want to maximize the number of establishments (including both small and large) so that robust model estimates can be obtained. We view the study as a pilot because it does not fully utilize the LRD, which contains annual panel data beginning in 1972. While the number of industries being studied is limited, and the data employed are far from perfect, use of these microdata can eliminate aggregation bias to allow generation of some meaningful results and, more important, provide good direction for future research.

Our primary findings are that (i) there are significant differences in the production technology between small and large establishments; and (ii) based on the scale parameter estimates, small establishments appear to be as efficient as large establishments under normal economic conditions. These findings suggest that, for the five industries under examination, large size is not a necessary condition for efficient production. However, small establishments seem to be unable to maintain constant returns to scale production during economic recessions such as that in 1982.

The remainder of the paper is organized as follows: Section II presents the model specification. Section III briefly discusses the data and estimation procedures. The empirical results, including the estimated production functions and scale economies are discussed in section IV. Section V gives a summary, conclusions, and statements of future research needs. Finally, the Appendix provides a detailed discussion of the data.

II. <u>MODEL SPECIFICATION</u>

We assume that there exists a production function that relates output and inputs such that

$$Q = F(X,Z), \tag{1}$$

where Q represents output; X is a vector of inputs, and Z is a vector of other relevant explanatory variables.

If Q is homogeneous of degree 8, then

$$F(X,Z)r^{8} = F(rX,Z), \tag{2}$$

where 8 is a constant and r is any positive real number. Assuming cost minimization and using the generalized Euler's theorem, we derive the following cost share equation system:[3]

$$S_i = P_i X_i \Big/ \sum_{i=1}^{k} P_i X_i = F_i X_i / \lambda F = \frac{\partial Q}{\partial X_i}\,\frac{X_i}{\lambda Q} = \frac{1}{\lambda}\left(\partial \ln Q / \partial \ln X_i\right) \qquad i = 1,2,\ldots k \tag{3}$$

where p_i is the price of input i and F_i = MF/MX_i.

For estimation, we need a specific functional form for F. Traditionally, applied production analysis has often been based on the Cobb-Douglas and Constant Elasticity of Substitution (CES) production functions.[4] However, it is generally recognized that these functional forms are highly restrictive; and therefore, when possible, a more flexible functional form should be preferred.[5]

During the last two decades, economists have developed and used several flexible functional forms. Such new functional forms include the transcendental logarithmic (translog) form,[6] the extended generalized Cobb-Douglas form,[7] and the symmetric generalized McFadden form.[8] Of these functional forms, the translog function is the most widely used in current empirical studies, especially in production, cost, and factor demand analyses. For one thing, the translog function is the simplest flexible functional form and has the smallest number of parameters to be estimated. Therefore, it is easier to estimate than other flexible forms.[9] Yet, like other flexible functional forms, it does not impose any <u>a priori</u> restrictions on the degree of substitution among the factors of production. Further, the translog function contains traditional functions as special cases. That is, when certain parameters are constrained, the translog function is reduced to the CES or the Cobb-Douglas function. Thus, a nested test can be developed for testing the validity of the Cobb-Douglas and CES functions and other hypotheses concerning the structure of production by using the translog model.

For this study we specify a three-factor translog production function including capital (K), labor (L), and M (materials including energy inputs) as the inputs in producing output (Q). In addition, we include two types of qualitative variables that may affect the production of individual establishments. These variables are designed to capture the effects of ownership type and of establishment size on production.

i) <u>Establishment type variables</u>

$$DT = \begin{cases} 1, & \text{if the establishment is owned by a firm that owns other establishments (a multi-plant firm)} \\ 0, & \text{otherwise} \end{cases}$$

ii) <u>Size variables</u>

$$SZ_{20} = \begin{cases} 1, & \text{if } 20 \leq TE < 50 \text{ employees} \\ 0, & \text{otherwise} \end{cases}$$

$$SZ_{50} = \begin{cases} 1, & \text{if } 50 \leq TE < 100 \text{ employees} \end{cases}$$

$\quad\quad 0$, otherwise

$$SZ_{100} = \begin{cases} 1, & \text{if } 100 \leq TE < 200 \text{ employees} \\ 0, & \text{otherwise} \end{cases}$$

$$SZ_{200} = \begin{cases} 1, & \text{if } TE \geq 200 \text{ employees} \\ 0, & \text{otherwise.} \end{cases}$$

where TE = total employees.

We have selected the smallest size class (5-19 employees) as the base size class. This is the smallest usable size class, because in the LRD the data for establishments with 1 - 4 employees are largely imputed based on administrative records and plants. Before proceeding, we want to emphasize that the terms "small" and "large" are relative. Therefore, it is impossible to offer a universally accepted definition for small and large establishments. Whether an establishment is small or large in a particular industry depends on the industry. For example, an automobile manufacturing plant that has 600 employees is small, whereas a dress manufacturer having 600 employees is large. Thus, instead of drawing a definite line between small and large, for each industry we classify production units into the above five employment size classes.

With the above variables, the KLM-translog production function can be written as follows

$$\begin{aligned} \ln(Q) = {} & \alpha_0 + \alpha_{DT}DT + \alpha_1 SZ_{20} + \alpha_2 SZ_{50} + \alpha_3 SZ_{100} + \alpha_4 SZ_{200} + \alpha_K \ln(K) \\ & + \alpha_L \ln(L) + \alpha_M \ln(M) + 0.5\alpha_{KK}(\ln K)^2 + 0.5\alpha_{LL}(\ln L)^2 + 0.5\alpha_{MM}(\ln M)^2 \\ & + \alpha_{KL}\ln(K)\ln(L) + \alpha_{KM}\ln(K)\ln(M) + \alpha_{LM}\ln(L)\ln(M) + \alpha_{KS20}SZ_{20}\ln(K) \\ & + \alpha_{KS50}SZ_{50}\ln(K) + \alpha_{KS100}SZ_{100}\ln(K) + \alpha_{KS200}SZ_{200}\ln(K) + \alpha_{LS20}SZ_{20}\ln(L) \\ & + \alpha_{LS50}SZ_{50}\ln(L) + \alpha_{LS100}SZ_{100}\ln(L) + \alpha_{LS200}SZ_{200}\ln(L) + \alpha_{MS20}SZ_{20}\ln(M) \\ & + \alpha_{MS50}SZ_{50}\ln(M) + \alpha_{MS100}SZ_{100}\ln(M) + \alpha_{MS200}SZ_{200}\ln(M). \end{aligned} \tag{4}$$

Cost minimization conditions (3) allow us to derive an input demand equation system by equating cost shares (S_m, m = K, L, M) to the logarithmic marginal products (i.e., first derivatives of the translog production function with respect to individual inputs) to obtain

$$S_K = \frac{1}{\lambda}[\alpha_K + \alpha_{KK}\ln(K) + \alpha_{KL}\ln(L) + \alpha_{KM}\ln(M) + \Sigma_i \alpha_{KSi}SZ_i] \tag{5}$$

$$S_L = \frac{1}{\lambda}[\alpha_L + \alpha_{LL}\ln(L) + \alpha_{KL}\ln(K) + \alpha_{LM}\ln(M) + \Sigma_i \alpha_{LSi}SZ_i]$$

$$S_M = \frac{1}{\lambda}[\alpha_M + \alpha_{MM}\ln(M) + \alpha_{KM}\ln(K) + \alpha_{LM}\ln(L) + \Sigma_i \alpha_{MSi}SZ_i],$$

where i = 20, 50, 100, 200.

Imposing homogeneity of degree 8 results in the following restrictions

$$"_K + "_L + "_M = 8 \qquad (5b)$$

and

$$"_{KK} + "_{KL} + "_{KM} = 0$$

$$"_{LL} + "_{KL} + "_{LM} = 0$$

$$"_{MM} + "_{KM} + "_{LM} = 0.$$

The returns to scale parameter, 8, can be directly estimated by substituting (9b) into (8) before estimating the model.

III. DATA AND ESTIMATION METHOD

1. DATA

For each of the five selected industries, we use confidential cross-section establishment level data extracted from the Census Bureau's LRD for 1977 and 1982. While cross-section data are subject to certain limitations, they also have some advantages for the purpose of this pilot study. In particular, for the most part, cross-section data reflect technology at a single time and thereby allow us to separate the effects of economies of scale from the effects of technological change. Another advantage of using data from the two Censuses is that it permits the examination of changes in economies of scale between the two Census years. The details on industry selection and data construction are discussed in the Appendix.

2. Estimation Procedures and Hypothesis Tests

There are two approaches to comparing the production technologies of large and small establishments. The first is to fit an overall production function, incorporating dummy size variables to allow both the intercept and slope of the function to vary among different size classes. The second approach is to approximate each segment of the actual production function.[10] That is, for each size class we fit a separate production function, allowing the production technology to differ across size classes. In this study, we apply the first approach to test whether or not there are differences in the production technologies of small and large establishments. If the test results indicate significant differences, we estimate production functions by size class and compare the results for small and large establishments.

For each size class as well as the whole industry, we estimate the production function jointly with the labor- and materials-share equations as a multivariate regression system,[11] using the Zellner's seemingly unrelated regression method (1962) as implemented in the SAS statistical package.[12] This procedure yields more efficient parameter estimates than those obtained from single equation methods because including the share-equations in the estimation results in additional degrees of freedom without adding any free parameters.

The full model, equations (8) and (9), can be used to construct various nested tests. For the purpose of this study we focus on testing the effects of (i) establishment size and of (ii) establishment type (single versus multi-unit establishments). In addition, it is important to test whether or not the translog function is preferred to the Cobb-Douglas function. Our hypothesis tests are structured as follows. We first estimate the full model (Model I). We then estimate a series of restricted models. To test for the establishment size effects Model II imposes $"_1 = "_2 = "_3 = "_4 = 0$ and $"_{iS20} = "_{iS50} = "_{iS100} = "_{iS200} = 0$. To test for the establishment type effects, Model III imposes $"_{DT} = "_{DK} = "_{DL} = "_{DM} = 0$. If all of these hypotheses are accepted, we then proceed with the Cobb-Douglas function, Model IV, with all the second order coefficients of the translog model being set to zero. That is, $"_{KK} = "_{LL} = "_{LM} = "_{KL} = "_{KM} = "_{LM} = 0$.[13]

Our nested tests are based on the Gallant-Jorgenson analog of the likelihood ratio test (1979), which is defined as $T^o = N*S(\hat{"},\hat{◊})_R - N*S(\tilde{"},\hat{◊})_U$,[14] where $S(\hat{"},\hat{◊})_R$ and $S(\tilde{"},\hat{◊})_U$ are the minimum values of the objective functions of the restricted and unrestricted models, respectively. N is the number of observations. T^o is distributed as P^2 with degrees of freedom equal to the number of restrictions (i. e., the number of parameters left out of the restricted model).

IV. <u>EMPIRICAL RESULTS</u>

1. <u>Hypotheses Test Results</u>

Table 1 reports the estimated values of the Jorgenson-Gallant analog of the likelihood ratio statistic, T^o. When the data are in accord with the null hypothesis (H_o), T^o will be smaller than the critical chi-square $P^2_{(df,1-")}$ and when they are not $T^o > P^2_{(df,1-")}$ and H_o will be rejected.

The table reports the results for three null hypotheses tests: (i) no establishment size effect, (ii) no establishment type effects, and (iii) the industries are characterized by the Cobb-Douglas technology.[15] As shown in the table, all values of T^o are substantially greater than the values of the critical P^2 and hence, all three hypotheses are strongly rejected.[16] This is so for all industries. Thus, based on our classification of establishments, the test results indicate that (i) establishments of different sizes have different production technologies, (ii) establishment types (single versus multi-unit establishments) have significant effects on production, and (iii) the Cobb-Douglas function is not a valid representation of the production technology of the industries under study.

2. <u>The Estimated Production Functions</u>

Before examining the estimates, it is important to know whether or not the underlying production function is "well-behaved." A "well-behaved" production function requires that output increases monotonically with all inputs and its isoquants are convex. Monotonicity implies that all the estimated cost shares of inputs are non-negative. The convexity condition is satisfied if the bordered Hessian matrix of the first and second derivatives is negative definite. For all 60 estimated production functions (10 overall and 50 by plant size), there are no statistically significant violations of these conditions when evaluated at the means.[17] This indicates the plausibility of the hypothesis that the parameters reflect long-run equilibria.[18]

The estimates of the ten overall production functions are reported in Table 2. While there are potential data problems (discussed in the Appendix), we find that the data fit the model very well. For all five industries, the conventional measure of goodness of fit, $\&^2$, is high. In addition, an analysis of residuals from each equation indicates that in general the fits were good.[19] All the estimated first and second order coefficients of the translog production functions are highly significant based on the conventional t-test. All the estimates for the returns to scale parameter, 8, are highly significantly different from zero, and the standard errors are at least 50 times smaller than the estimated coefficients, indicating a high degree of precision of the estimates.

We now turn to the interpretation of the results obtained from the size class regressions reported in 3a - 3e. Comparing these estimates with those obtained from the overall functions, we find that the two sets of estimates are identical in signs. First, all estimates of the first-order coefficients ("$_{i}$) are positive and highly significant throughout 50 disaggregated regressions and 10 overall regressions. Second, except for "$_{LM}$, all the estimates of the second-order coefficients ("$_{ij}$) are positive and significant at the .01 percent level. For "$_{LM}$, all estimates are negative and highly significant. Finally, all the estimates of the scale parameter, 8, are positive and highly significantly different from zero.

The effects of establishment types (single versus multi-unit) differ across size-classes, industries, and years. As indicated by the estimates of "$_{T}$ reported in the Tables, of the five industries, industry 2711 (Newspapers) is the only one that shows strong effects of multi-unit establishments (both small and large) on production: except for size class 1, the estimates of "$_{T}$ for all size classes are positive and statistically significant. For industry 3573 (Electronic Computing Equipment), there is no statistical evidence of positive effect of multi-unit establishments.[20] For industries 2335 (Dresses) and 2511 (Furniture), small multi-unit establishments (99 employees or less) appear to be more productive relative to single-unit establishments of the same sizes. Beyond that size, the effects of multi-unit establishments on production are either significantly negative or nearly zero. Finally, the results for industry 3662 (Radio & TV Communication Equipment) are mixed. However, large multi-unit establishments, again, do not show any significant effects on production. Overall, except for one case (SIC 2711), the results obtained from regressions by size class suggest that small establishments in multi-unit firms are somewhat more productive than small single-unit firm. It is possible that this result is due to measurement error because we do not include central (administrative) office resources in the establishments of multi-unit firms, whereas such resources are included in single-unit establishments. However, large establishments (200 employees or more) in multi-unit firms are not more productive than large single unit firms.

Finally, while we do not report the regional results in this paper, we note that in our preliminary work we incorporated regional variables into the model, and found that the results were very poor: only a few of 80 regional coefficients are significant at the five percent level.[21] Moreover, excluding these regional dummy variables did not alter the estimated values of the main coefficients of the model. To some extent, the insignificance of these variables is comforting. It appears that the estimated technical coefficients of the production function are robust and invariant with respect to the inclusion or exclusion of the regional variables.[22]

The foregoing results (together with the Gallant-Jorgenson test) indicate that it is appropriate to estimate the production functions disaggregated by plant size classes. Disaggregated production analysis provides more information regarding the structure of production of establishments in various size classes, in particular returns to scale.[23]

3. <u>Economies of Scale</u>

Table 4 reports the scale parameter estimates obtained directly from estimating separate production functions by size class for each industry in both years 1977 and 1982. The numbers in parentheses below each estimate are $t_{.01}$ * standard errors, which are used to construct the confidence interval for the true parameter (i.e., $\beta = \tilde{\beta} \pm t_{.01}$ * standard error).

Considering first the 1977 scale parameter estimates we found that all the estimates for the largest size class and four of the five estimates for the smallest size class are statistically insignificantly different from one. For industry 3662 (Radio and TV), while smallest establishments exhibit increasing returns to scale, relatively small establishments with 50 employees can achieve constant returns to scale.

In terms of long-run average cost curves, the 1977 estimates imply that industry 3573 (electronic computing equipment) had a constant horizontal cost curve, while industry 3662 (Radio & TV) had a flat L-shaped curve. For the other industries, industries 2335 (Dresses) and 2711 (Newspapers) appear to have horizontal average cost curves even though establishments with 20-49 employees in 2335 and those with 50-99 employees in 2711 exhibit decreasing returns to scale. We note, however, that the diseconomies result is somewhat surprising and could be a consequence of random variations because it appears unlikely that diseconomies occur at such relatively small size classes. For the furniture industry (sic 2711), smallest and largest establishments were equally efficient while medium-sized establishments (50-199 employees) experienced diseconomies. Again, this result could be a consequence of random variations. These results indicate that in 1977 both small and large establishments in the five industries under study are capable of achieving constant returns to scale and thereby are equally efficient in production.

In contrast to the 1977 estimates, the 1982 estimated scale parameters show that, except for the newspapers industry (SIC 2711), all smallest establishments were inefficiently operated on the declining portion of the industry average cost curve. On the other hand, except for the furniture industry (SIC 2511), all largest establishments appear to efficiently operate on the flat region of the average cost curve.

In terms of cost curves, the implied average cost curves of the dresses (SIC 2335) and electronic computing equipment (SIC 3573) industries changed their shape from horizontal to L-shaped curves. This means that in 1982 small establishments (less than 100 employees) in these industries were less efficient than larger ones. The 1982 average cost curve of the furniture industry (2511) became the traditional U-shaped curve, but the efficient size was relatively small (20 employees), while largest establishments operated on the increasing portion of the average cost curve. The shape of the cost curves of the radio & TV (3662) and newspaper (2711) industries does not appear to change from 1977 to 1982.

We note that the newspaper industry is the only one in which both small and large establishments were equally efficient in production in both years. This result is consistent with Litman (1988), who states that the newspaper industry has made great technical progress during the 70's and 80's by combining new developments in the printing sector with breakthroughs from computer, telecommunication and photography industries.[24] These developments have significantly improved speed and efficiency throughout the production process, which in turn reduce labor input. Our results are also consistent with other findings by Litman that the long-run average cost of the newspaper industry has become "flatter across a wide range of different circulation and issue sizes. This lowers the barrier to entry associated with scale economies and permits small- and medium-sized papers to become more cost competitive with their larger brethren" (1988, pp. 30-31).

In summary the scale estimates obtained from the production function functions disaggregated by plant size for the five industries under study suggest that:

(i) Both the largest establishments (200 or more employees) and smallest establishments (5-19 employees) appear to be equally efficient in 1977.

(ii) In 1982, except for the newspaper industry, small establishments experienced economies of scale and operated on the declining portion of the long-run average cost curve, while larger establishments were able to produce with constant returns to scale. One possible explanation for this is that, long-run average cost curves for large establishments were relatively flat so that these establishments could adjust their scale of operations and still maintain constant returns to scale in response to the decrease in the demand for their products in the recession year. Small establishments, on the other hand, had little to adjust. These small establishments could only minimize short-run average costs on the declining portion of the industry long-run average cost curve.

Overall, these results appear to suggest that under normal economic conditions (such as in 1977) small establishments are as efficient as large establishments. However, during recessions small establishments appear to be less able to adjust their scale of operation and still maintain efficient levels of production.

V. CONCLUDING REMARKS AND AREAS OF FUTURE RESEARCH

The purpose of this study is to assess the possibility of differences in the production technologies of small and large establishments in the U.S. manufacturing sector, based on a sample of five 4-digit industries. We focus on estimating of returns to scale in various establishment size classes.

The study is unique in that it is based on confidential plant-level data extracted from the Census Bureau's Longitudinal Research Database, the richest data set currently available for the study of small and large manufacturers. In particular, the data provide the most comprehensive information available on outputs and inputs of "small" and "large" establishments, as well as location, and other identifying variables.

While the data set is valuable for empirical research such as ours, as with most data sets it is far from perfect. One limitation is that it does not contain information on input and output prices. As a result, real inputs and outputs cannot be measured accurately. Most importantly, our data set does not provide sufficient data for constructing an accurate and theoretically sound measure of capital services. Instead, it provides data on capital stocks based on book values, which are generally not an appropriate proxy for capital input. This inaccurate measure of capital input may cause biases in the model parameter estimates.

In spite of these problems, the data fit our model well and the estimated degrees of returns to scale can be considered relatively robust. Based on our classification of plant size, the overall results for the five industries under study indicate that there are significant differences in the production technologies among establishments of different plant sizes, suggesting that production analysis by plant size is an appropriate approach. We also found that, ceteris paribus, small establishments owned by multi-unit firms are somewhat more productive than small single-unit firms. It is possible that this result is due to measurement error because we may fail to include central office resources in the establishments of multi-unit firms. However, large establishments owned by multi-unit firms are not more productive than single-unit firms.

Finally but most importantly, our scale parameter estimates indicate that for the industries we studied, under normal economic conditions, small establishments appear to be as efficient as large establishments. However, this result did not hold in general for 1982, a recession year. With the exception of the newspaper industry, small establishments were unable to maintain constant returns to scale technology during the 1982 economic recession and were perhaps more affected by the recession than large establishments. One possible explanation is that because of their small capacity, small establishments had little to adjust in response to the decline in the demand for their products caused by the 1982 recession, and were forced to operate on the declining portion of the long run average cost.

The above results seem to suggest that a large establishment size is not a necessary condition for efficient production. We want, however, to emphasize that while the above conclusions are drawn with certain degree of confidence, they are by no means definite. This is in part because we have studied only five selected industries. Moreover, because these industries (by design) have large numbers of small establishments, their technologies and market conditions may naturally allow small establishments to survive. In addition, as mentioned repeatedly in the text, our data are subject to limitations, and the constructed variables such as capital input may contain measurement errors. Finally, we selected the years 1977 and 1982 census years simply because data were available for many more small plants for these years. However, as 1982 was a recession year, it may not have been a good year on which to base the study because the recession may have affected the economic behavior of the establishments under examination. For example, product demand may not have been sufficient in 1982 to allow production at capacity (minimum average cost). If so, and if these affects varied across size classes, then efficiency comparisons made across size classes in 1982 may be invalid.

The above limitations suggest several areas for additional research. One important area is to improve the data. In this regard, it is useful to construct panel data files, linking the establishment data for all the years covered by the LRD)) currently, 1972-1986. Panel data would allow us to construct an improved measure of capital stock which, together with measures of capacity utilization, can be used to obtain estimates of capital services.[25] It may also be possible to at least account partially for the vintage of capital by using data on establishment history.[26]

A final important area of additional research is to refine the models. This grows out of the improved data sets described above. With panel data available one can specify dynamic models that account separately for the effects of such important events as technical change and business cycles. With these models, one can test whether these events affect large and small establishments differently, as our current models seem to suggest.

Table 1: Hypothesis Test Results: Values of T^o-Statistics

	Model I vs. Model II H_0: No size effects r = 12 $P^2_{c(12,99)}$ = 26.20		Model I vs Model III H_0: No type effects r = 1 $P^2_{c(3,99)}$ = 6.63		Model I vs Model IV H_0: Cobb-Douglas Technology r = 3 $P^2_{c(3,99)}$ = 11.30	
	1977	1982	1977	1982	1977	1982
SIC 2335	1468	1633	1425	1513	37076	23989
SIC 2511	673	790	660	755	12179	11149
SIC 2711	3088	2528	2471	2195	33239	24794
SIC 3573	339	838	303	823	7078	11917
SIC 3662	996	1268	819	1081	13609	20487

Note: T^o = N * $S(ʌ,ṽ)_R$ - N * $S(ʺ,ṽ)_u$, where $S(ʌ,ṽ)_R$ is the minimum value of the objective function of the restricted model (R), and $S(ʺ,ṽ)_u$ is the minimum value of the objective function of the unrestricted model (u). N is the number of observations, r is the number of restrictions.

Table 2
Parameter Estimates of the Translog KLM-Production Functions
by Industry
(Asymptotic Standard errors in parentheses)

Parameters	SIC 2335		SIC 2511		SIC 2711		SIC 3573		SIC 3662	
	1977	1982	1977	1982	1977	1982	1977	1982	1977	1982
"$_{0}$	1.966*	1.679*	1.783*	1.741*	1.782*	1.600*	1.874*	2.054*	1.742*	1.875*
	(.030)	(.031)	(.058)	(.054)	(.034)	(.034)	(.105)	(.080)	(.058)	(.058)
"$_{L}$	.604*	.630*	.530*	.549*	.547*	.540*	.583*	.640*	.590*	.626*
	(.003)	(.003)	(.007)	(.008)	(.004)	(.005)	(.015)	(.013)	(.009)	(.009)
"$_{M}$	.257*	.214*	.202*	.178*	.233*	.225*	.156*	.145*	.158*	.155*
	(.003)	(.002)	(.005)	(.005)	(.002)	(.003)	(.012)	(.009)	(.007)	(.007)
"$_{LL}$	.175*	.136*	.143*	.126*	.112*	.103*	.134*	.140*	.142*	.137*
	(.002)	(.003)	(.004)	(.004)	(.002)	(.002)	(.006)	(.005)	(.004)	(.004)
"$_{MM}$	.159*	.132*	.193*	.193*	.130*	.133*	.204*	.186*	.193*	.182*
	(.001)	(.001)	(.003)	(.003)	(.001)	(.001)	(.005)	(.003)	(.003)	(.003)
"$_{LM}$	-.140*	-.104*	-.106*	-.096*	-.047*	-.049*	-.104*	-.094*	-.108*	-.090*
	(.001)	(.001)	(.003)	(.002)	(.001)	(.001)	(.004)	(.003)	(.003)	(.002)
8	.966*	1.102*	.962*	1.009*	1.004*	1.065*	1.031*	1.029*	1.049*	1.047*
	(.008)	(.010)	(.014)	(.012)	(.008)	(.008)	(.021)	(.016)	(.013)	(.012)
"$_{T}$	.026	.103*	.109*	.036*	.058*	.071*	.006	.054	.046*	.021
	(.016)	(.024)	(.017)	(.017)	(.010)	(.009)	(.033)	(.028)	(.018)	(.018)
"$_{S20}$	.032*	-.154*	.031	-.013	-.075*	-.025	.003	-.006	-.075*	.016
	(.015)	(.016)	(.024)	(.025)	(.014)	(.015)	(.070)	(.048)	(.035)	(.035)
"$_{S50}$	.010	-.216*	.093*	.035	-.029	-.021	-.062	-.077	-.083*	-.015
	(.019)	(.024)	(.033)	(.035)	(.022)	(.022)	(.077)	(.056)	(.042)	(.041)
"$_{S100}$	-.006	-.313*	.096*	-.020	.066*	.029	-.105	-.088	-.184*	-.009
	(.027)	(.036)	(.042)	(.044)	(.030)	(.030)	(.085)	(.067)	(.050)	(.049)
"$_{S200}$	-.010	-.456*	.089	-.043	.251*	.015	-.138	-.072	-.094	.034
	(.040)	(.057)	(.054)	(.055)	(.038)	(.038)	(.108)	(.080)	(.062)	(.060)
"$_{LS20}$	.013*	.005	.016*	.004	.003	.022*	.037*	.019	.009	.023*
	(.004)	(.005)	(.005)	(.005)	(.003)	(.003)	(.014)	(.011)	(.008)	(.007)
"$_{LS50}$	.003	.019*	.012*	.013	.012*	.024*	.025	.013	.013	.019*
	(.004)	(.007)	(.006)	(.007)	(.004)	(.005)	(.014)	(.011)	(.008)	(.007)
"$_{LS100}$	.005	.0004	.027*	.008	.026*	.042*	.007	.005	.002	.034*
	(.006)	(.011)	(.007)	(.008)	(.005)	(.005)	(.015)	(.013)	(.009)	(.008)
"$_{LS200}$	-.000	-.058*	.021*	.010	.065*	.064*	.010	.013	.049*	.058*
	(.008)	(.017)	(.006)	(.008)	(.005)	(.006)	(.014)	(.011)	(.009)	(.008)

Table 2 (Continued)
Parameters Estimates of the Translog KLM-Production Functions
by Industry
(Asymptotic Standard errors in parentheses)

Parameters	SIC 2335		SIC 2511		SIC 2711		SIC 3573		SIC 3662	
	1977	1982	1977	1982	1977	1982	1977	1982	1977	1982
"$_{MS20}$	-.009*	.009*	-.004	.001	-.008*	-.011*	-.007	-.005	.005	-.008
	(.004)	(.003)	(.004)	(.004)	(.002)	(.002)	(.012)	(.008)	(.006)	(.005)
"$_{MS50}$	.001	-.001	-.004	-.000	-.011*	-.019*	-.007	-.007	.0006	-.006
	(.005)	(.004)	(.005)	(.005)	(.002)	(.002)	(.012)	(.008)	(.006)	(.006)
"$_{MS100}$	-.003	.016*	-.011	-.010	-.020*	-.029*	.002	.0004	.014*	-.019*
	(.006)	(.006)	(.006)	(.006)	(.003)	(.003)	(.012)	(.009)	(.007)	(.007)
"$_{MS200}$	-.002	.031*	-.017*	-.001	-.035*	-.037*	-.000	-.009	-.023*	-.033*
	(.009)	(.011)	(.006)	(.006)	(.003)	(.003)	(.011)	(.008)	(.006)	(.007)
Adjusted R^2										
RnQ	.928	.916	.971	.969	.964	.965	.961	.953	.968	.963
SL	.915	.811	.672	.607	.469	.399	.634	.644	.593	.548
SM	.933	.869	.883	.832	.857	.781	.884	.842	.838	.823
Number of observations (N)										
	1976	2560	1008	1170	3261	3265	454	928	1062	1342

* Denote "Statistically significant" (different from zero) at the five (or less) percent level.

Table 3a
Parameter Estimates of the Translog KLM-Production Functions
(Asymptotic standard errors in parentheses)
Women's, Misses', and Juniors' Dresses (SIC 2335)

Parameters	Size Class 1		Size Class 2		Size Class 3		Size Class 4		Size Class 5	
	1977	1982	1977	1982	1977	1982	1977	1982	1977	1982
"$_0$	1.929*	1.589*	2.039*	1.495*	1.964*	1.550*	1.790*	1.746*	1.582*	2.445*
	(.036)	(.041)	(.056)	(.066)	(.098)	(.145)	(.186)	(.283)	(.252)	(.588)
"$_L$	.602*	.625*	.618*	.633*	.611*	.653*	.605*	.630*	.607*	.558*
	(.003)	(.004)	(.003)	(.003)	(.004)	(.005)	(.006)	(.011)	(.014)	(.050)
"$_M$	.249*	.210*	.245*	.223*	.266*	.211*	.255*	.236*	.268*	.227*
	(.003)	(.002)	(.003)	(.002)	(.005)	(.004)	(.007)	(.010)	(.015)	(.025)
"$_{LL}$	.189*	.126*	.179*	.154*	.164*	.142*	.180*	.160*	.163*	.060*
	(.003)	(.006)	(.002)	(.005)	(.003)	(.006)	(.004)	(.010)	(.009)	(.030)
"$_{MM}$	.166*	.143*	.162*	.126*	.151*	.131*	.151*	.122*	.147*	.129*
	(.002)	(.002)	(.002)	(.002)	(.003)	(.003)	(.004)	(.005)	(.006)	(.009)
"$_{LM}$	-.143*	-.108*	-.143*	-.102*	-.137*	-.102*	-.137*	-.099*	-.115*	-.083*
	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)	(.003)	(.005)	(.005)	(.013)
8	.975*	1.130*	.957*	1.110*	.969*	1.082*	.997*	1.038*	1.034*	.944*
	(.010)	(.013)	(.014)	(.017)	(.021)	(.030)	(.034)	(.052)	(.039)	(.092)
"$_T$	.140*	.193*	.009	.051	.052	.168*	.047	.069	-.112*	-.090
	(.037)	(.051)	(.031)	(.043)	(.031)	(.044)	(.040)	(.056)	(.051)	(.141)
Adjusted R^2										
RnQ	.915	.834	.804	.819	.782	.777	.822	.759	.883	.695
SL	.930	.774	.910	.824	.889	.849	.945	.788	.907	.679
SM	.951	.865	.926	.873	.910	.889	.955	.843	.916	.900
Numbers of observations (N)										
	515	1080	787	942	423	361	172	137	79	40

* Denote "Statistically significant" (different from zero) at the five (or less) percent level.

Table 3b
Parameter Estimates of the Translog KLM-Production Functions
(Asymptotic standard errors in parentheses)
Wood Household Furniture Industry (SIC 2511)

Parameters	Size Class 1 1977	Size Class 1 1982	Size Class 2 1977	Size Class 2 1982	Size Class 3 1977	Size Class 3 1982	Size Class 4 1977	Size Class 4 1982	Size Class 5 1977	Size Class 5 1982
α_0	1.877*	1.535*	1.213*	1.506*	2.323*	2.210*	2.939*	2.029*	1.749*	2.629*
	(.111)	(.077)	(.129)	(.120)	(.242)	(.265)	(.326)	(.293)	(.143)	(.198)
α_L	.522*	.520*	.523*	.551*	.571*	.599*	.601*	.607*	.594*	.661*
	(.011)	(.011)	(.011)	(.013)	(.012)	(.020)	(.018)	(.022)	(.015)	(.025)
α_M	.219*	.187*	.208*	.181*	.178*	.194*	.135*	.110*	.144*	.085*
	(.008)	(.007)	(.007)	(.009)	(.009)	(.014)	(.013)	(.017)	(.013)	(.019)
α_{LL}	.137*	.111*	.128*	.123*	.165*	.153*	.175*	.147*	.173*	.167*
	(.007)	(.006)	(.008)	(.007)	(.008)	(.011)	(.012)	(.011)	(.009)	(.011)
α_{MM}	.167*	.192*	.196*	.196*	.204*	.168*	.242*	.210*	.245*	.252*
	(.005)	(.005)	(.005)	(.005)	(.006)	(.008)	(.007)	(.008)	(.008)	(.009)
α_{LM}	-.102*	-.091*	-.096*	-.095*	-.119*	-.091*	-.140*	-.131*	-.127*	-.130*
	(.005)	(.004)	(.004)	(.004)	(.006)	(.007)	(.008)	(.008)	(.006)	(.008)
λ	.938*	1.053*	1.078	1.051*	.886*	.935*	.808*	.973*	.994*	.912*
	(.027)	(.017)	(.026)	(.023)	(.042)	(.044)	(.050)	(.043)	(.019)	(.025)
α_T	.187*	-.042	.076*	.050	.152*	.133*	.042	.020	-.009	-.003
	(.051)	(.040)	(.033)	(.034)	(.035)	(.042)	(.038)	(.034)	(.027)	(.037)
Adjusted R^2										
ℓnQ	.827	.882	.844	.851	.728	.705	.679	.785	.913	.837
SL	.666	.558	.648	.686	.749	.669	.731	.606	.659	.517
SM	.857	.826	.892	.871	.934	.752	.929	.855	.900	.897
Numbers of observations (N)										
	262	397	275	340	179	166	118	119	174	148

* Denote "Statistically significant" (different from zero) at the five (or less) percent level.

Table 3c
Parameter Estimates of the Translog KLM-Production Functions
(Asymptotic standard errors in parentheses)
Newspapers Industry (SIC 2711)

Parameters	Size Class 1 1977	Size Class 1 1982	Size Class 2 1977	Size Class 2 1982	Size Class 3 1977	Size Class 3 1982	Size Class 4 1977	Size Class 4 1982	Size Class 5 1977	Size Class 5 1982
"$_0$	1.797*	1.742*	1.529*	1.253*	2.367*	1.728*	2.128*	1.512*	2.093*	1.858*
	(.050)	(.060)	(.082)	(.077)	(.196)	(.141)	(.276)	(.230)	(.109)	(.116)
"$_L$	.548*	.529*	.550*	.569*	.552*	.534*	.560*	.602*	.618*	.600*
	(.006)	(.009)	(.007)	(.007)	(.010)	(.017)	(.016)	(.018)	(.016)	(.019)
"$_M$	.219*	.219*	.233*	.207*	.232*	.209*	.249*	.201*	.150*	.219*
	(.003)	(.004)	(.003)	(.004)	(.006)	(.006)	(.009)	(.007)	(.011)	(.014)
"$_{LL}$	.116*	.099*	.109*	.110*	.093*	.086*	.101*	.108*	.131*	.107*
	(.003)	(.005)	(.005)	(.004)	(.006)	(.006)	(.009)	(.008)	(.007)	(.007)
"$_{MM}$	.138*	.132*	.118*	.121*	.119*	.149*	.130*	.163*	.155*	.162*
	(.002)	(.002)	(.002)	(.002)	(.004)	(.003)	(.005)	(.003)	(.006)	(.007)
"$_{LM}$	-.057*	-.053*	-.037*	-.051*	-.032*	-.050*	-.029*	-.053*	-.078*	-.044*
	(.002)	(.002)	(.002)	(.002)	(.004)	(.003)	(.005)	(.003)	(.005)	(.005)
8	1.001*	1.031*	1.043*	1.130*	.895*	1.033*	.950*	1.089*	.989*	1.023*
	(.013)	(.014)	(.017)	(.016)	(.035)	(.024)	(.043)	(.035)	(.013)	(.013)
"$_T$	.014	.011	.036*	.072*	.104*	.095*	.151*	.076*	.079*	.133*
	(.014)	(.017)	(.016)	(.014)	(.028)	(.019)	(.038)	(.029)	(.030)	(.038)
Adjusted R^2										
RnQ	.785	.797	.762	.781	.533	.691	.586	.698	.937	.940
SL	.545	.308	.386	.457	.437	.356	.348	.395	.433	.357
SM	.844	.755	.829	.761	.816	.823	.850	.864	.760	.857
Number of observations (N)										
	1319	964	910	1126	478	545	264	310	290	320

* Denote "Statistically significant" (different from zero) at the five (or less) percent level.

Table 3d
Parameter Estimates of the Translog KLM-Production Functions
(Asymptotic standard errors in parentheses)
Electronic Computing Equipment Industry (SIC 3573)

Parameters	Size Class 1 1977	Size Class 1 1982	Size Class 2 1977	Size Class 2 1982	Size Class 3 1977	Size Class 3 1982	Size Class 4 1977	Size Class 4 1982	Size Class 5 1977	Size Class 5 1982
α_0	2.304*	1.415*	2.149*	1.927*	1.590*	.590	1.290*	1.305*	1.698*	2.562*
	(.223)	(.149)	(.313)	(.290)	(.398)	(.348)	(.399)	(.404)	(.272)	(.193)
α_L	.672*	.538*	.616*	.671*	.560*	.615*	.596*	.656*	.592*	.703*
	(.033)	(.025)	(.034)	(.021)	(.027)	(.026)	(.025)	(.021)	(.023)	(.017)
α_M	.111*	.200*	.114*	.156*	.190*	.149*	.152*	.135*	.160*	.080*
	(.032)	(.016)	(.024)	(.014)	(.022)	(.015)	(.018)	(.019)	(.023)	(.016)
α_{LL}	.193*	.102*	.137*	.147*	.111*	.116*	.133*	.145*	.138*	.157*
	(.019)	(.012)	(.020)	(.011)	(.014)	(.013)	(.013)	(.009)	(.009)	(.007)
α_{MM}	.223*	.177*	.202*	.163*	.184*	.176*	.203*	.182*	.210*	.212*
	(.021)	(.009)	(.017)	(.007)	(.011)	(.007)	(.009)	(.009)	(.008)	(.006)
α_{LM}	-.127*	-.070*	-.126*	-.089*	-.085*	-.089*	-.109*	-.106*	-.105*	-.113*
	(.015)	(.006)	(.013)	(.006)	(.010)	(.007)	(.009)	(.007)	(.007)	(.005)
λ	.936*	1.141*	.975*	1.054*	1.063*	1.248*	1.100*	1.123*	1.037*	.970*
	(.053)	(.032)	(.060)	(.054)	(.064)	(.056)	(.058)	(.058)	(.032)	(.023)
α_T	.098	.094*	.049	.065	-.063	.038	.046	.072	-.033	.053
	(.066)	(.048)	(.060)	(.062)	(.052)	(.058)	(.054)	(.059)	(.094)	(.065)
	Adjusted R^2									
ℓnQ	.850	.884	.628	.606	.735	.727	.799	.759	.847	.857
SL	.706	.502	.582	.601	.469	.593	.711	.747	.628	.694
SM	.826	.734	.804	.788	.841	.787	.910	.860	.925	.923
	Numbers of observations (N)									
	56	147	79	220	84	161	76	116	159	284

* Denote "Statistically significant" (different from zero) at the five (or less) percent level.

Table 3e
Parameter Estimates of the Translog KLM-Production Functions
(Asymptotic standard errors in parentheses)
Radio & TV Trans., Signal., & Det. Equip. Industry (SIC 3662)

Parameters	Size Class 1		Size Class 2		Size Class 3		Size Class 4		Size Class 5	
	1977	1982	1977	1982	1977	1982	1977	1982	1977	1982
"$_{0}$	1.457*	1.408*	1.208*	1.813*	1.518*	1.057*	1.395*	1.801*	2.004*	2.299*
	(.163)	(.144)	(.150)	(.153)	(.254)	(.264)	(.351)	(.337)	(.145)	(.130)
"$_{L}$	.606*	.596*	.541*	.630*	.611*	.640*	.584*	.671*	.648*	.649*
	(.016)	(.019)	(.015)	(.016)	(.015)	(.015)	(.016)	(.019)	(.022)	(.020)
"$_{M}$	.152*	.161*	.194*	.144*	.155*	.154*	.157*	.130*	.110*	.142*
	(.012)	(.017)	(.008)	(.009)	(.013)	(.013)	(.015)	(.013)	(.018)	(.017)
"$_{LL}$	.150*	.117*	.104*	.127*	.144*	.132*	.134*	.147*	.162*	.136
	(.009)	(.009)	(.010)	(.008)	(.009)	(.008)	(.009)	(.009)	(.009)	(.007)
"$_{MM}$	.189*	.173*	.177*	.187*	.189*	.177*	.207*	.188*	.215*	.185*
	(.007)	(.010)	(.005)	(.005)	(.008)	(.007)	(.009)	(.005)	(.007)	(.006)
"$_{LM}$	-.115*	-.084*	-.088*	-.091*	-.109*	-.088*	-.113*	-.095*	-.125*	-.091*
	(.007)	(.007)	(.005)	(.005)	(.007)	(.006)	(.007)	(.006)	(.007)	(.006)
8	1.124*	1.163*	1.134*	1.056*	1.077*	1.179*	1.069*	1.052*	.994*	.986*
	(.040)	(.032)	(.029)	(.028)	(.044)	(.043)	(.053)	(.049)	(.017)	(.014)
"$_{T}$	.037	-.141*	.014	.069*	.039	.019	.097*	.048	.093	.027
	(.051)	(.051)	(.031)	(.030)	(.035)	(.038)	(.046)	(.040)	(.057)	(.048)
Adjusted R^2										
RnQ	.823	.824	.808	.764	.679	.711	.688	.669	.925	.928
SL	.631	.604	.588	.556	.584	.568	.621	.572	.524	.433
SM	.865	.785	.837	.832	.821	.822	.857	.863	.822	.822
Numbers of observations (N)										
	157	223	289	363	204	260	158	189	254	307

* Denote "Statistically significant" (different from zero) at the five (or less) percent level.

Table 4
Scale Parameter Estimates

Size class	SIC 2335 1977	SIC 2335 1982	SIC 2511 1977	SIC 2511 1982	SIC 2711 1977	SIC 2711 1982	SIC 3573 1977	SIC 3573 1982	SIC 3662 1977	SIC 3662 1982
5-19	.975[C]	1.130[I]	.938[C]	1.053[I]	1.001[C]	1.031[C]	.936[c]	1.141[1]	1.124[I]	1.163[I]
	(±.026)	(±.033)	(±.069)	(±.044)	(±.033)	(±.036)	(±.136)	(±.082)	(±.103)	(±.082)
20-49	.957[D]	1.110[I]	1.078[I]	1.051[C]	1.043[C]	1.130[I]	.975[C]	1.054[C]	1.134[I]	1.056[C]
	(±.036)	(±.044)	(±.067)	(±.059)	(±.044)	(±.041)	(±.155)	(±.139)	(±.075)	(±.072)
50-99	.969[C]	1.085[I]	.886[D]	.935[C]	.895[D]	1.033[C]	1.063[C]	1.248[I]	1.077[C]	1.179[I]
	(±.054)	(±.077)	(±.108)	(±.113)	(±.090)	(±.062)	(±.165)	(±.144)	(±.113)	(±.111)
100-199	.997[C]	1.038[C]	.808[D]	.973[C]	.950[C]	1.089[C]	1.100[C]	1.123[C]	1.069[C]	1.052[C]
	(±.088)	(±.134)	(±.129)	(±.111)	(±.111)	(±.090)	(±.149)	(±.149)	(±.137)	(±.126)
200 or more	1.034[C]	.944[C]	.994[C]	.912[D]	.989[C]	1.023[C]	1.037[C]	.970[C]	.994[C]	.986[C]
	(±.100)	(±.237)	(±.049)	(±.064)	(±.033)	(±.033)	(±.082)	(±.059)	(±.044)	(±.036)

Note: The number in parentheses are $\pm t_{.01}$ standard errors, which are used to construct confidence intervals for the true parameters.

[C] denotes "insignificantly different from 1" at the one percent level (constant returns to scale).

[D] denotes "significantly less than 1" at the one percent level (decreasing returns to scale).

[I] denotes "significantly greater than 1" at the one percent level (increasing returns to scale).

FOOTNOTES

1. Starr (1988) summarizes recent data on this issue, citing recent studies.

2. For more details on the selection of the industries, see Nguyen and Reznek (1988).

3. For a derivation of the generalized Euler's theorem, see Chiang (1974). An advantage of the cost minimization model (over the profit maximization approach) is that cost minimization does not require the assumption of perfect competition in the product (output) market.

4. See the classic papers by Cobb and Douglas (1928), and Arrow, Chenergy, Minhas and Solow (1961).

5. While a general Cobb-Douglas function does allow the estimation of variable returns to scale, it is based on the assumption that the elasticity of substitution between any two factors of production equals one (e.g., "$_{KL}$ + "$_{KM}$ + "$_{LM}$ = 1). This assumption is arbitrary and unreasonable; and it does not allow the examination of the differences in the ways in which establishments of different sizes utilize their factors of production. Similarly, in the context of more than two inputs, the CES function implies that the partial elasticity of substitution between all pairs of inputs are equal (e.g., "$_{KL}$ = "$_{KM}$ = "$_{LM}$). Therefore, it rules out the possibility of complementarity between any pair of inputs. For more details on this point, see Uzawa (1962), Berndt and Christensen (1973), and Burgess (1975), for example.

6. See Christensen, Jorgenson, and Lau (1971). Applied studies using this form include those by Berndt and Wood (1975), Burgess (1975) Christensen and Green (1979), Kokkelenberg and Nguyen (1989), and others.

7. This functional form was explored by Magnus (1979) and later employed by Guilkey, Lovell, and Sickles (1983).

8. Developed by Diewert and Wales (1987) and is based on McFadden (1978).

9. In a recent empirical study, Kokkelenberg and Nguyen (1987) used establishment data extracted from the Census Bureau's Longitudinal Research Database (LRD) to estimate the above three flexible functions. They concluded that "the translog function is the easiest to work with in terms of achieving convergence, in producing plausible results, and in overall forecasting ability." Guilkey, Lovell and Sickles (1983) also found similar results.

10. This approach was applied by Nerlove (1963), and Christensen and Green (1979).

11. Because the three cost shares add to one, estimating all three share equations together results in a singular covariance matrix. The problem can be avoided by deleting one share-equation from the estimation procedure. Here we delete the capital share equation because data on capital input are less reliable than data on labor and materials. The estimates of the parameters in the capital equation can be derived from the estimates of the production function and the other two share-equations, using formula 5b. Recently Dhrymes (1989) suggests using the generalized inverse (g-inverse) of the singular covariance matrix in the Aiken minimand, rather than disposing of one equation. Unfortunately, a computer program for this procedure is not yet available.

12. See SES Institute (1984) Chapter 20, which describes the SAS/ETS SYSNLIN procedure. We used SES version 5.18 on Digital Equipment Corporation Microvax II minicomputer. Kmenta and Gilbert (1968) showed that the Zellner estimates will converge to the efficient maximum likelihood estimates. For the small sample properties, Zellner (1963) also showed that his estimates are unbiases and efficient relative to ordinary least squares estimates.

13. For more details on these test see Nguyen and Reznek (1989).

14. For an example of this test, see Gallant (1987): p 459.

15. Refer to Chart 1 and the discussion at the end of Section III for more details on the scheme of hypothesis tests.

16. We also used the likelihood ratio test as programmed in the Time Series Processor (TSP) econometric package and obtained similar results.

17. The monotonicity condition is satisfied at all data points (i.e., there are no negative cost shares). For the convexity condition, the Hessian bordered matrix is negative definite when evaluated at the means.

18. While not universally accepted, the common interpretation of the parameter estimates based on cross-section data is that they portray long-run behavior. Intriligator (1978) states that "time-series data usually reflect short-run behavior while cross-section reflect long-run behavior, in particular, a greater adjustment to long-run equilibrium" (p 64, n 5). Also see Kuh (1963). For a discussion of difficulties of making inferences about the dynamics of change from cross-sectional results, see Hsiao (1986).

19. Residual analysis basically checks whether the residuals follow normal distributions and whether there are outliers that could significantly influence the parameter estimates. For most of our equations, the distributions of residulas did appear to reasonably close to normal based on the tests available in SAS PROC UNIVARIATE (See SAS Institute Inc, 1985, Chapter 54). There were some outliers in several of our equations; however based on visual inspection they probably are not influential (although we did not conduct formal tests for influential observations). We do not report the residual analysis here because of space considerations and because there are possible issues involving confidentiality of respondent data.

20. Of the ten estimated coefficients, only one is significant at the five percent level; but it could be a consequence of random variations.

21. We introduced dummy variables representing 8 census regions: (1) Middle Atlantic, (2) East North Central, (3) West North Central, (4) South Atlantic, (5) East South Central, (7) Mountain, and (8) Pacific. New England was used as the base.

22. This does not mean that location has no effects on industrial production, nor does it mean that output prices, labor quality, technical efficiency or the like are the same in all regressions. On the contrary, each of these factors could have significant effects on industrial production, but in different directions and could offset one another, causing the insignificance of the dummy variables. Formal tests for these effects require specific data and models that are beyond the scope of this pilot study.

23. In the case of simple linear regressions, it is straightforward to evaluate the effect of dummy variables on the slope of the

function. In the translog model, however, the evaluation is complex, in particular, it must be evaluated at each data point, and the evaluation involves actual data. Therefore, it is difficult to determine precisely how establishment sizes affect production based on the slope coefficients of the dummy variables. As already mentioned, our purpose of estimating the overall functions, incorporating sixe dummy ariables, is to construct a related test for differences among establishment sof different size classes. The test results indicate that there are significant differences among establishments of different sizes and hence justify our estimating separate regressions by size class.

24. These technical developments include computerization of the massage stage, cold type photocomposition and paste up, offset processes, and satellite delivery of facsimile pages.

25. In this regard, it would be appropriate to take advantage of a recent method developed by Dhrymes (1989) that (a) does not require that the number of yearly observations on all plants be equal, and (b) can handle breaks in the annual time series of observations on dividual plants. This work has been done as part of Dhrymes' current ASA/NSF/Census Research Fellowship at the Census Bureau.

26. Data on establishment history were colelcted in the 1975 and 1981 ASM's; for a description, see U.S. Bureau of the Census (1985, p 54). The Center for Economic studies has begun to explore these data.

REFERENCES

Arrow, K., H.B. Chenery, R. Minhas, and R.M. Solow (1961), "Capital-labor Substitution and Economic Efficiency," Review of Economic and Statistics 43:228-232.

Berndt, E.R., and L.R. Christensen (1973), "The Translog Function and the Substitution of Equipment, Structures, and Labor in U.S. Manufacturing 1929-68," Journal of Econometrics, 1:81-114.

______________ and D. O. Wood (1975), "Technology, Price, and the Derived Demand for Energy," The Review of Economics and Statistics 67:259-268.

Brock, W.A., and D.S. Evans (1986), The Economics of Small Business: Their Role and Regulation in the U.S. Economy, (New York, N.Y. Holmes and Meier Publishers).

Burgess D.F. (1975), "Duality Theory and Pitfalls in the Specification of Technologies," Journal of Econometrics, 3:105-121.

Chiang, A.C. (1974), Fundamental Methods of Mathematical Economics, Second Edition, McGraw-Hill Book Company, New York.

Cobb, C.W., and P.H. Douglas (1928), "A Theory of Production," American Economic Review, 18:139-65.

Christensen, L.R. and W.H. Greene (1979), "Economies of Scale in U.S. Electric Power Generation," Journal of Political Economy, 84:655-676.

Christensen, L.R., D.W. Jorgenson, and L.J. Lau (1971), "Conjugate Duality and the Transcendental Logarithmic Production Function," Econometrica, 39:255-266.

Dhrymes, P.J. (1989), "Autoregressive Errors in Singular Systems of Equations" unpublished paper presented at the Center for Economic Studies Seminar on April 13, 1989.

Diewert, W.E. and T.J. Wales (1987), "Flexible Functional Forms and Global Curvature Conditions," Econometrica, 55:43-68.

Gallant, A.R. (1987), Nonlinear Statistical Models, New York, NY: John Wiley & Sons.

Gallant, A.R. and D.W. Jorgenson (1979), "Statistical Inferences for a System of Simultaneous, Non-linear, Implicit Equations in the Context of Instrumental Variable Estimation," Journal of Econometrics, 11: 275-302.

Guilkey, D.K., C.A.K. Lovell, and R.C. Sickles (1983), "A Comparison of the Performance of Three Flexible Functional Forms," International Economic Review, 24:591-616.

Hsiao, C. (1986), Analysis of Panel Data, New York, N.Y.: Cambridge University Press.

Intriligator, M.D. (1978) Econometric Models, Techniques, and Applications Englewood Cliff, N.J.: Prentice Hall, Inc.

Kmenta J., and R.F. Gilbert (1968), "Small Sample Properties of Alternatives Estimators of Seemingly Unrelated Regressions," Journal of the American Statistical Association, 63:1180-1200.

Kokkelenberg, E.C. and S.V. Nguyen (1987), "A Comparison of Three Flexible Functional Cost Forms Using Plant Level Data," Paper presented at the 1987 American Economic Association Conference in Chicago, December 1987.

_______________ (1989), "Modelling Technical Program and Multifactor Productivity: A Plant Level Example," Journal of Productivity Analysis, 1:69-90.

Kuh, E. (1963), Capital Stock Growth: A Micro-Econometric Approach, North Holland.

Litman, B. (1988), "Microeconomic Foundations," in Press Concentration and Monopoly: New Perspectives on Newspaper Ownership and Operation, edited by R.G. Picard, J.P. Winter, M.E. McContes, and S. Lacy, Norwood, NJ: Albex Publishing Corporation: 3-34.

McFadden, D. (1978), "The General Linear profit Function," in Production Economics: A Dual Approach to Theory and Application, Vol. 1, edited by M. Fuss and D. McFadden, Amsterdam: North-Holland:269-286.

McGuckin, R., and G. Pascoe (1988), "The Longitudinal Research Database: Status and Research Possibilities," Survey of Current Business, November, pp. 30-37.

Magnus, J.R. (1979), "Substitution Between Energy and Non-Energy in the Netherlands 1950-1976," International Economic Review, 20:465-484.

Nerlove, M. (1963), "Returns to Scale in Electricity Supply," in Measurement in Economics -- Studies in Mathematical Economics in Memory of Yehuda Grunfeld, edited by Carl F. Christ, Stanford, Calif: Stanford University Press.

Nguyen, S.V. and A. Reznek (1988), "Selecting Industries for the Study of Small firms versus large firms in the U.S. Manufacturing Sector." A Report prepared for the Small Business Administration, November 16, 1988.

_______________ (1989), Production Technologies Economies of Scale and Factor Substitution in Large and Small U.S. Manufacturing Establishments: A Pilot Study, Report submitted to the U.S. Small Business Administration, October 1989.

SAS Institute Inc. (1984), SAS/ETS Users Guide Version 5 Edition, Cary, NC: SAS Institute, Inc.

_______________ (1985), SAS Users Guide: Basics, Version 5 Edition, Cary, NC: SAS Institute Inc.

Starr, E. (1988), "Small Business in Manufacturing," Business Economics, 2:41-45.

U.S. Bureau of the Census (1985), "Longitudinal Establishment Data Documentation," Unpublished Manuscript.

U.S. Government Printing Office (1987), The State of Small Business A Report of the President to the Congress 1987, Washington D.C.: U.S. Government Printing Office.

Usher, D. (1980), The Measurement of Capital, National Bureau of Economic Research, The University of Chicago Press, Chicago and London.

Uzawa, A.J. (1962), "Production Functions with Constant Elasticities of Substitution," Review of Economic Studies: 291-299.

Varian, H. R. (1984), Microeconomic Analysis. New York: W.W. Norton, (2nd Edition).

Zellner, A. (1962), "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias," Journal of American Statistical Association, 57:348-68.

_______________ (1963), "Estimators of Seemingly Unrelated Regressions: Some Exact Finite Samples Results," Journal of American Statistical Association, 58:977-92.

APPENDIX: INDUSTRY SELECTION AND DATA CONSTRUCTION

The data employed in this study are extracted from the Census Bureau's Longitudinal Research Data Base (LRD) described by McGuckin and Pascoe (1988). The LRD consists of linked data from the Census Bureau's Annual Survey of Manufacturing (ASM) and Census of Manufactures. Currently, the data for 1972 through 1986 are in the LRD; data from the Censuses of Manufactures for 1963 and 1967 have been linked to the LRD as well.

For this pilot study, we use only two cross sections, taken from the 1977 and 1982 Censuses of Manufactures. While the Censuses contain establishment data for 450 four-digit industries, we select only five 4-digit SIC industries. Our selection criteria are: (1) the selected industries should have a sufficient number of both large and small establishments that robust estimates of the model parameters can be obtained, and (2) the establishments within the industries should produce relatively homogeneous products so that meaningful comparisons can be made.

For the five industries, most of the size classes have substantially more than 100 observations (establishments) except for size class 5 (Total employment greater than 200) in SIC 2335 which has only 40 establishments in 1982. Also, all the five industries have product specialization and coverage ratios that are well above 90%. This means that (1) the establishments in all of our five industries produce relatively homogeneous products, in the sense that most of the products they produce are classified as being in these industries; and (2) the establishments classified as being in our industries produce most of the output of products that are classified as coming from these industries. In what follows we describe the constructed variables that are used to estimate the production duration.

Output, Q, is defined as total shipments (TVS) plus changes in inventories of finished goods and work-in-process. That is

$$Q = TVS + (FIE - FIB) + (WIE - WIB)$$

where FIB and FIE are finished goods inventories at the beginning and end of year, whereas WIB and WIE denote work-in-process inventories at the beginning and end of year, respectively. All of the right hand side variables are taken directly from the LRD data base.

Labor input: Although the Census of Manufacturing provides data on both total number of employees (TE) and total worker hours (PH), we use the latter because it is a better measure of labor input. Ideally, we should separate labor input into that provided by production and non-production workers. We cannot make this separation directly because the Census of Manufactures does not provide it. Fortunately, data on wages of production and non-production workers are reported separately; in addition, data on total supplemental labor costs are available. From these components, we can derive a measure of production worker equivalent hours as follows:

The average production worker wage rate is

$$PL = WW/PH$$

where WW is total production worker wages and PH is total production worker hours. The estimate of total plant worker hours (L) is then calculated as

$$L = (WW + OW)/PL$$

where OW is wages paid to non-production workers. The measure L assumes that relative wages are proportional to marginal productivity.

Capital input: This measure is, as with most studies in applied production analysis, probably the weakest variable in the data set. The ideal measure is of capital services--since output is measured as units of goods per unit of time (per year in our case), capital should be measured as machine hours per year (Varian 1984 p. 172). An ideal capital services measure should recognize that the same number of machines may be used more or less intensively (and thus we need some measure of capacity utilization), and that machines of different vintages may provide different levels of services because they embody different technologies. To obtain a measure of capital services, the usual procedure is to (1) measure the real value of capital stock by deflating by a price index, and (2) to adjust this deflated capital stock with a utilization rate. A procedure often used to obtain deflated value of capital stock is the perpetual inventory method as discussed by Usher (1980). Ideally, these deflators and utilization rates should be specific to each plant.

For this pilot study, as a practical matter we simply measure gross capital stocks based on book values of building and machinery assets for each plant (which we call GSK, or gross capital stock,) as the sum of gross building stock (GSB) and gross machinery stock (GSM):

GSK = BAE + MAE,

where BAE and MAE are building machinary assets at the end of the year, respectively.

In light of the above discussion, our measure may be subject to important measurement errors. First, the data are reported in book values that do not accurately reflect the value of capital; in addition, building and machinery assets are imputed for establishments that are not part of the ASM sample. Second, use of a simple sum of building and machinery assets assumes that these components of capital are homogeneous; this is obviously incorrect. Third, there is no adjustment for differences (either across time or across establishments) in the quality of capital. Fourth, there is no adjustment for intensity of use.

Although we recognize the shortcomings, it is difficult to see how the problems could have been handled in the context of cross-sectional analysis. As stated above, it is possible to construct a consistent time series measure of capital stock based on the perpetual inventory method using data available in all the years covered by the LRD that are relevant to this study (1972-1982; in fact, though, the LRD now has data through 1986). However, this method can only be applied directly to establishments that are in the ASM sample for all the years. This eliminates a large number of small establishments because of the way the ASM sample is selected (for details, see U.S. Bureau of the Census 1985, section 3). Thus, to construct an improved capital input measure will take a great deal of time and effort; it must be a major part of future work.

Materials input: Total materials (M) consumed are broken into the following components:

M = CP + EE + CF + CW,

where CP denotes values of materials and parts purchased, EE denotes values of purchased electricity, CF denotes valued of fuels consumed in production, and CW denotes values of contract work.

Total labor cost (SSL) is the sum of production worker wages (WW), nonproduction worker wages (OW), and supplemental labor costs (LC):

SSL = WW + OW + LC.

Total production cost (PCOST) is the sum of capital (GSK), labor (SSL) and materials (M) costs,

PCOST = GSK + SSL + M.

It follows that the three cost share variables are defined as: Production

SK = GSK/PCOST

SL = SSL/PCOST

SM = M/PCOST

where SK, SL, and SM are cost shares of capital, labor, and materials, respectively. By definition, SK + SL + SM = 1.

1. Starr (1988) summarizes recent data on this issue, citing recent studies.

2. For more details on the selection of the industries, see Nguyen and Reznek (1988).

3. For a derivation of the generalized Euler's theorem, see Chiang (1974). An advantage of the cost minimization model (over the profit maximization approach) is that cost minimization does not require the assumption of perfect competition in the product (output) market.

4. See the classic papers by Cobb and Douglas (1928), and Arrow, Chenery, Minhas and Solow (1961).

5. While a general Cobb-Douglas function does allow the estimation of variable returns to scale, it is based on the assumption that the elasticity of substitution between any two factors of production equals one (e.g., $F_{KL} = F_{KM} = F_{LM} = 1$). This assumption is arbitrary and unreasonable; and it does not allow the examination of the differences in the ways in which establishments of different sizes utilize their factors of production. Similarly, in the context of more than two inputs, the CES function implies that the partial elasticity of substitution between all pairs of inputs are equal (e.g., $F_{KL} = F_{KM} = F_{LM}$). Therefore, it rules out the possibility of complementarity between any pair of inputs. For more details on this point, see Uzawa (1962), Berndt and Christensen (1973), and Burgess (1975), for example.

6. See Christensen, Jorgenson, and Lau (1971). Applied studies using this form include those by Berndt and Wood (1975), Burgess (1975) Christensen and Greene (1979), Kokkelenberg and Nguyen (1989), and others.

7. This functional form was explored by Magnus (1979) and later employed by Guilkey, Lovell, and Sickles (1983).

8. Developed by Diewert and Wales (1987) and is based on McFadden (1978).

9. In a recent empirical study, Kokkelenberg and Nguyen (1987) used establishment data extracted from the Census Bureau's Longitudinal Research Database (LRD) to estimate the above three flexible functions. They

concluded that "the translog function is the easiest to work with in terms of achieving convergence, in producing plausible results, and in overall forecasting ability." Guilkey, Lovell and Sickles (1983) also found similar results.

10. This approach was applied by Nerlove (1963), and Christensen and Green (1979).

11. Because the three cost shares add to one, estimating all three share equations together results in a singular covariance matrix. The problem can be avoided by deleting one share-equation from the estimation procedure. Here we delete the capital share equation because data on capital input are less reliable than data on labor and materials. The estimates of the parameters in the capital equation can be derived from the estimates of the production function and the other two share-equations,using formula 5b. Recently Dhrymes (1989) suggests using the generalized inverse (g-inverse) of the singular covariance matrix in the Aiken minimand, rather than disposing of one equation. Unfortunately, a computer program for this procedure is not yet available.

12. See SAS Institute (1984) Chapter 20, which describes the SAS/ETS SYSNLIN procedure. We used SAS version 5.18 on Digital Equipment Corporation Microvax II minicomputer. Kmenta and Gilbert (1968) showed that the Zellner estimates will converge to the efficient maximum likelihood estimates. For the small sample properties, Zellner (1963) also showed that his estimates are unbiased and efficient relative to ordinary least squares estimates.

13. For more details on these test see Nguyen and Reznek (1989).

14. For an example of this test, see Gallant (1987):p. 459.

15. Refer to Chart 1 and the discussion at the end of Section III for more details on the scheme of hypothesis tests.

16. We also used the likelihood ratio test as programmed in the Time Series Processor (TSP) econometric package and obtained similar results.

17. The monotonicity condition is satisfied at all data points (i.e., there are no negative cost shares). For the convexity condition, the Hessian bordered matrix is negative definite when evaluated at the means.

18. While not universally accepted, the common interpretation of the parameter estimates based on cross-section data is that they portray long-run behavior. Intriligator (1978) states that "time-series data usually reflect short-run behavior while cross-section reflect long-run behavior, in particular, a greater adjustment to long-run equilibrium" (p. 64, n.5). Also see Kuh (1963). For a discussion of difficulties of making inferences about the dynamics of change from cross-sectional results, see Hsiao (1986).

19. Residual analysis basically checks whether the residuals follow normal distributions and whether there are outliers that could significantly influence the parameter estimates. For most of our equations, the distributions of residuals did appear to reasonably close to normal based on the tests available in SAS PROC UNIVARIATE (See SAS Institute Inc, 1985, Chapter 54). There were some outliers in several of our equations; however based on visual inspection they probably are not influential (although we did not conduct formal tests for influential observations). We do not

report the residual analysis here because of space considerations and because there are possible issues involving confidentiality of respondent data.

20. Of the ten estimated coefficients, only one is significant at the five percent level; but it could be a consequence of random variations.

21. We introduced dummy variables representing 8 census regions:(1) Middle Atlantic, (2) East North Central, (3) West North Central, (4) South Atlantic, (5) East South Central, (7) Mountain, and (8) Pacific. New England was used as the base.

22. This does not mean that location has no effects on industrial production, nor does it mean that output prices, labor quality, technical efficiency or the like are the same in all regressions. On the contrary, each of these factors could have significant effects on industrial production, but in different directions and could offset one another, causing the insignificance of the dummy variables. Formal tests for these effects require specific data and models that are beyond the scope of this pilot study.

23. In the case of simple linear regressions, it is straightforward to evaluate the effect of dummy variables on the slope of the function. In the translog model, however, the evaluation is complex, in particular, it must be evaluated at each data point, and the evaluation involves actual data. Therefore, it is difficult to determine precisely how establishment sizes affect production based on the slope coefficients of the dummy variables. As already mentioned, our purpose of estimating the overall functions, incorporating size dummy variables, is to construct a related test for differences among establishments of different size classes. The test results indicate that there are significant differences among establishments of different sizes and hence justify our estimating separate regressions by size class.

24. These technical developments include computerization of the massage stage, cold type photocomposition and paste up, offset processes, and satellite delivery of facsimile pages.

25. In this regard, it would be appropriate to take advantage of a recent method developed by Dhrymes (1989) that (a) does not require that the number of yearly observations on all plants be equal, and (b) can handle breaks in the annual time series of observations on individual plants. This work has been done as part of Dhrymes' current ASA/NSF/Census Research Fellowship at the Census Bureau.

26. Data on establishment history were collected in the 1975 and 1981 ASM's; for a description, see U.S. Bureau of the Census (1985, p 54.). The Center for Economic studies has begun to explore these data.